Advanced Point Cloud Filtering Algorithm for Enhanced Accuracy in Mountainous Terrain Surveying and Mapping

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This study investigates the practical application of an enhanced point cloud filtering algorithm in mountainous terrain surveying and mapping. The author introduces a tailored algorithm specifically designed for such areas. The research begins with a critical analysis of the limitations of existing point cloud filtering algorithms, which often result in suboptimal ground-point cloud systems after filtering. The proposed methodology systematically examines non-ground points in point clouds and classifies surface cover types. The method effectively identifies and removes non-ground points by utilizing well-established algorithms, particularly for vegetation and building extraction, significantly improving the point cloud filtering process. Rigorous qualitative and quantitative analyses demonstrate substantial improvements, comparing the proposed algorithm with the progressive encryption triangulation filtering algorithm. The ground point cloud generated by the improved algorithm closely aligns with the measured profile, showing minimal deviation, with an average elevation difference of -0.06 m and a mean square error of 0.45 m. In contrast, the progressive encryption triangulation filtering algorithm shows a mean difference of -0.45 m and a mean square error of 0.71 m. This research concludes that the improved point cloud filtering method, based on surface coverage types, outperforms the gradually encrypted triangulation filtering algorithm in terms of accuracy. The proposed algorithm demonstrates approximately a 45% improvement in accuracy compared to traditional methods. Furthermore, the proposed approach offers superior applicability, increased automation, and enhanced extraction accuracy in mountainous terrains compared to conventional ground-point filtering methods. These findings provide innovative solutions for the complex challenge of point cloud filtering in rugged mountainous areas, advancing surveying and mapping methodologies.

Povzetek: Članek predstavi izboljšan algoritem za filtriranje oblakov točk, prilagojen kartiranju goratih terenov, ki povečuje kvaliteto filtriranja, avtomatizacijo in zmogljivost pri obdelavi kompleksnih geografskih podatkov.

1 Introduction

In recent years, laser scanning has become one of the most common methods for obtaining 3D point clouds. Laser scanning has wide applications in 3D reconstruction, cultural relic protection, reverse engineering, and geographic surveying. Subsequent processing work, the accuracy of registration, and the quality of 3D reconstruction can be affected by noise in the 3D point cloud obtained through the scanner. Therefore, it is necessary to filter the point cloud model. Statistical filtering and bilateral filtering are the two main types of filtering algorithms used for 3D point clouds. Statistical filtering removes noise points, while bilateral filtering corrects the position of noise points. Surveying and mapping professionals widely apply 3D laser scanning technology in the field due to its fast, efficient, non-contact, dynamic, and precise characteristics, as well as its ability to digitize, automate, and provide real-time data. In terms of work efficiency, labor intensity, cost control, personnel and equipment investment, and controllability of the construction period, both field data collection and indoor data processing have achieved significant results, and the measurement results meet the requirements of large-scale topographic map aerial photogrammetry specifications.

Figure 1 depicts the application of an improved point cloud filtering algorithm in mountainous terrain surveying and mapping. The advantage of 3D laser scanning technology is that it avoids the drawbacks of traditional single-point measurement and combines the lightweight flexibility of drones with the maturity of laser scanning equipment technology, making the adaptability of drone airborne 3D laser scanning to the environment more extensive. It can achieve real-time and accurate batch collection of surface information data and has advantages that traditional manual measurement and aerial photogrammetry cannot compare. In recent years, through theoretical research and practical verification by domestic and foreign scholars, relevant theories related to radar data processing have become increasingly mature. We propose a two-stage filtering strategy from coarse to fine to fill terrain in large areas of missing data.

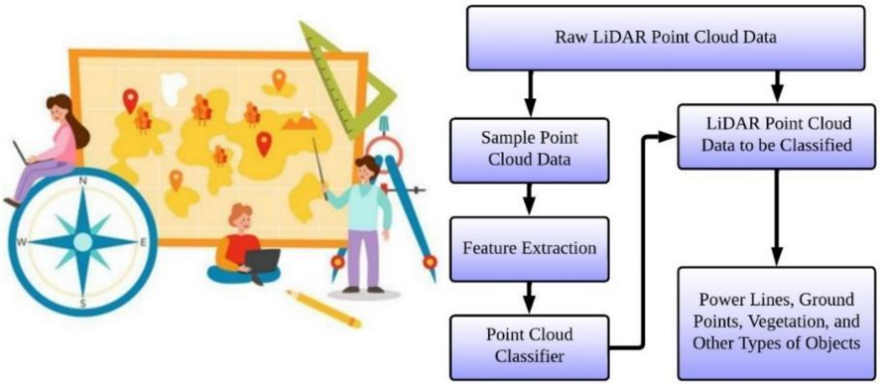

Figure 1: Application of improved point cloud filtering algorithm in mountainous terrain surveying and mapping

This strategy starts with morphological filtering to address excessively corroded terrain and combines it with region growth. This box graph detection method takes point cloud attribute information and processes it. It speeds up point cloud filtering, cuts down on ground point cloud miss points, and quickly extracts non-ground points, which also cuts down on point cloud filtering miss points. We compared and studied the cloth simulation filtering algorithm, the progressive triangular network filtering algorithm, and the CSF algorithm. The results showed that the progressive triangular network filtering algorithm had the smallest error and completed the filtering process faster in areas with complex terrain undulations.

Constructing point cloud adaptive filtering and directional intelligent precise editing software achieves reliable, efficient, and robust intelligent filtering and the DEM Poisson editing method for image-dense matching point cloud data. The triangle network progressive encryption filtering method based on multiple primitives has the best overall performance when compared to other point cloud filtering algorithms. With the increasing maturity of theoretical research and the rapid development of software and hardware equipment, the application of unmanned aerial vehicle (UAV) airborne 3D laser scanning technology in topographic mapping has been widely practiced [1, 2]. The application of 3D laser scanning technology for surveying and mapping purposes in mountainous regions presents a substantial obstacle attributable to the constraints of current point cloud filtering algorithms. Traditional approaches, which use the lowest point in the grid as the ground seed, inadequately extract ground points with precision, resulting in distorted terrain representations. The inadequacy of existing filtering algorithms hampers the accuracy and applicability of 3D laser scanning technology in mountainous regions, particularly in the context of surveying and mapping. An inventive methodology is urgently required to address the constraints of conventional methods and enable automated and more accurate point cloud filtering in difficult terrains. The present study presents an innovative point cloud filtering algorithm that utilizes surface coverage categories as its foundation. This algorithm deviates from traditional assumptions and capitalizes on well-established algorithms intended for extracting vegetation and buildings. By addressing the inherent difficulties of mountainous terrains, the proposed method provides a more precise and automated approach to filtering point clouds. The study adds to the body of research by showing that the new algorithm is more accurate and useful than existing progressive encryption triangulation filtering methods. It does this through both qualitative and quantitative analyses. The study's objective is to establish a foundation for enhanced 3D laser scanning implementations in mountainous areas, thereby making a significant contribution to the progression of surveying and mapping technologies. The rest of the paper is organized as the most recent work is discussed in Section 2, and the adopted methodology is discussed in Section 3. The experimental analysis is presented in Section 4, followed by the Conclusion in Section 5.

2 Literature review

As an active and non-contact Earth observation system, 3D laser scanning has made a huge step forward from measuring a single point to measuring the whole surface. It can quickly and automatically get high-precision 3D geospatial data on targets. 3D laser pulses have strong penetrability and can penetrate gaps between vegetation to generate multiple echoes, obtaining true 3D point clouds on the surface. Point cloud filtering is the process of extracting ground points from laser point clouds, which is the foundation and key of point cloud processing and plays a crucial role in the production and application of subsequent digital 3D products. After more than ten years of development, scholars both domestically and internationally have proposed various classic filtering algorithms, such as mathematical morphology filtering algorithms, slope-based filtering algorithms, progressive encryption triangulation filtering methods, moving surface fitting filtering algorithms, robust interpolation filtering methods (linear least squares interpolation method), boundary clustering filtering methods, etc. However, most filtering algorithms mainly target flat terrain and sparse vegetation areas, which exhibit significant terrain fluctuations. The filtering effect of point clouds in mountainous areas with complex terrain is poor.

For filtering complex terrain areas in mountainous areas, Wang *et al.* combined echo information to construct a multi-level filtering method, which improved the accuracy of point cloud filtering in mountainous areas. However, the algorithm design is complex, and the operational efficiency is low [3]. Chen *et al.* proposed a progressive encryption triangulation filtering algorithm that can handle various complex forest scenes, especially in areas with variable terrain and environments [4]. Its advantage lies in its ability to preserve mountain peaks, handle broken lines and steep slopes, and perform well in different forest areas. A motor drives the 3D laser scanner to rotate and emit laser pulses at high speed. Thick pseudo-error point clouds often wrap around ground objects due to factors such as ranging error, angle measurement error, attitude error, etc. In practice, the above mountainous filtering algorithm significantly improves the filtering accuracy of point clouds in mountainous areas [5]. However, it has been found that when using the gradual encryption of triangular or square grids to extract ground points, multiple selections of the lowest point within the grid as the starting seed point can easily lead to mistakenly extracting the error point cloud as ground points in mountainous terrain with significant changes in micro terrain [6]. This results in the classified ground point cloud being lower than the true surface.

The technology of using the 3D laser to obtain point clouds and extract regular objects such as buildings, power facilities, and vegetation is very mature. Researchers have widely published algorithms that extract vegetation on the surface using laser point clouds based on morphology, resulting in increasingly refined parameters [7, 8]. A large number of scholars have studied single tree extraction, estimation of forest tree biomass, centimeter-level height measurement of low vegetation, estimation of shrub grassland biomass, and extraction of growth parameters for typical crops such as sorghum, corn, rice, and sugar beet. Compared with the diversity of landforms, vegetation has a more significant spatial form recognition ability, and the extraction accuracy is better than that of point cloud filtering [9]. To explore a new filtering method suitable for point clouds in mountainous areas, the author first divides the area according to the type of surface coverage and retains the point cloud without processing for exposed surfaces. Existing mature nonground point cloud extraction algorithms are utilized to extract and eliminate nonground points for buildings and various types of vegetation surface cover types, thus achieving point cloud filtering [10, 11]. This effectively breaks through the theoretical assumption that the local lowest point is an accurate ground point in existing filtering algorithms, resulting in point clouds being pulled down and feature areas being missing after filtering in complex terrain areas, forming a unified filtering process and improving the degree of filtering automation, maximizing the preservation of characteristic terrain, and improving filtering accuracy.

3 Methods

In this section, the research introduces a two-fold methodology to address the limitations of traditional point cloud filtering in mountainous terrains. An algorithm improvement strategy is presented, leveraging surface coverage types to enhance non-ground point elimination. Next, we will detail the iterative operations of the improved algorithm, which include trend surface fitting and slope discrimination, to achieve optimal terrain point cloud extraction.

3.1 Algorithm improvement

While the relevant algorithms have shown promise in tests, they may not work well in real life because of things like different terrains and landforms, thick vegetation, and laser radar that doesn't go deep enough. Bad processing can cause a lot of small peaks to show up on the model's surface, making the results not good enough. The accuracy of point cloud data at the edge of the airstrip is often poor, which can lead to small elevation differences between the point clouds of two airstrips in overlapping areas. Improper processing can lead to uneven DEM models. Therefore, based on the trajectory file, the author uses TerraSolid software to eliminate redundant point cloud data. The author separated terrain points and object points, improved slope secondary discrimination, and made it possible to process terrain point cloud data more precisely by making the grid trend surface and elevation interpolation fitting algorithm better. This maximizes the elimination of small peaks on the DEM surface, reduces the workload of manual intervention, and makes the generated DEM model smoother.

Carefully analyzing the filtering and classification processing mechanisms of point cloud data, based on relevant theoretical research results, and considering the terrain and vegetation coverage of the survey area, we construct an improved algorithm [12]. Interpolate, fit, and grid the redundant point cloud data to obtain the center point elevation of each grid, thus acquiring a relatively rough initial trend surface. The weight of elevation points within the grid relative to the grid center elevation is related to the plane distance of its center (specifically, the smaller the distance, the greater the weight), resulting in a trend of surface elevation between vegetation points and surface points when obtained through fitting. The threshold is related to the grid size; therefore, by setting a reasonable threshold, iterative algorithms can be used to effectively filter vegetation points. The point cloud data between continuously changing terrain and abrupt terrain has a positive or negative relative trend surface, which may lead to over-filtering or insufficient filtering of the point cloud in this area. Based on this, the author uses the linear interpolation method to fit the fitted elevation of the ground 3D point cloud in the trend surface and uses it as the reference elevation for height difference calculation. As the fitted trend surface is similar to the actual terrain, the fitted elevation does not differ significantly from the original elevation. The fitted trend surface effectively eliminates the adverse effects of continuously changing terrain on filtering [13, 14] by ensuring that the elevation difference is not mistakenly filtered out due to sudden changes in terrain. The calculation formula is shown in Equation 1.

$$G_k = \frac{\sum H_i \times (\sqrt{2 \times \frac{L}{2} \_ DI}}{\sum_{ik} (\sqrt{2 \times \frac{L}{2} \_ DI}} \tag{1}$$

In the formula, H_i is the fitting elevation of point I, L is the size of the grid, DI is the plane distance from the point to the center of the grid, G_k is the interpolation elevation of the grid, and K is the number of grids. The degree of mixing between vegetation points and terrain points is greater for areas covered by low vegetation. Using only elevation difference for point cloud filtering and classification cannot completely separate terrain points from terrain points. Therefore, in this area, if the threshold of elevation difference is set too large, low vegetation points are easily recognized as terrain points; If the threshold of elevation difference is set too small, it will cause some terrain points to be filtered out. The size of the slope is one of the indicator factors for judging terrain changes. The author introduces secondary discrimination of slope as an additional condition to further improve the point cloud filtering and recognition ability of terrain points, thereby obtaining real terrain point cloud data in low vegetation areas, to meet the requirements of large-scale terrain production. The author uses the slope algorithm to re-judge the point cloud data filtered by the trend surface elevation, which can further avoid the problem of identifying terrain points as terrain points and reduce the problem of over-filtering terrain points. In slope filtering, it is necessary to ensure that the filtered 3D point cloud data does not participate in the next calculation. The detailed calculation formula for the secondary discrimination of slope is shown in Equation 2.

$$\mathrm{S}_i = \frac{(H_i - H_{ci})}{\sqrt{(X_i - X_{ci})2 + (y_i - y_{ci})^2}} \tag{2}$$

3.2 Iterative operation of improved algorithms

The trend surface fitting, linear interpolation, and slope discrimination involved in the above-improved algorithms need to be achieved through iterative algorithms. This article uses MATLAB programming to achieve the iterative operation of the algorithm. In iterative operations, the key parameters involved include grid size and empirical threshold. The size of the grid changes continuously with iterative operations. In the initial calculation, a relatively large grid size is used to obtain a relatively rough trend surface. As the number of iterations increases, the grid size is gradually adjusted until a fine-trend surface model that is closer to the real ground is obtained. During this period, the upper and lower limits of grid size are crucial and need to be determined based on the terrain of the experimental area and the density of 3D point cloud data. Since the testing area is located in a mountainous area and the terrain is relatively complex, to ensure that some terrain filtering is not eliminated, the upper limit of the grid size cannot be set too large. The lower limit of the grid size is related to the point cloud data density of the testing area, and the setting requirement is to ensure that there is at least one point in each grid.

The empirical threshold is the threshold for the difference between the fitted elevation of 3D ground points and the measured elevation. The determination of its value is related to the size of the grid, and the larger the grid, the greater the threshold. Each input of empirical threshold data is the result of the previous iterative filtering. To effectively achieve slope discrimination, the trend elevation of 3D points is subtracted from the actual elevation in iterative operations. If the elevation difference is not within the threshold range, it indicates that the point is a non-ground point; If the elevation difference is within the threshold range, further calculate the slope. When the slope is greater than the threshold, it indicates that the point is nonground; When the slope is less than the threshold, it indicates that the point meets the size requirements set by the grid window and is recognized as a ground point. By repeatedly calculating and continuously adjusting the size of the grid, it is ensured that the filtered points no longer participate in the next iteration calculation. The detailed iteration steps are as follows:

i. Set the initial grid window size. Interpolate the point cloud data, and obtain the elevation of each grid by weighted linear interpolation of the distance between points in Equation 1, thereby obtaining a relatively rough initial trend surface.

ii. Linearly interpolate 3D point cloud data into the initial trend surface to obtain its trend surface elevation, and subtract the point cloud trend surface elevation from the true elevation. If the difference is greater than the threshold, it is considered a nonground point; If the difference is much lower than the threshold, the point is considered a gross error and is removed; If the difference is within the set threshold range, proceed to the next slope calculation [15].

iii. Calculate the slope of the grid center where the point cloud is located. When the slope is greater than the threshold, it indicates that the point is nonground; When the slope is within the threshold range, it is classified as an unclassified point cloud; If the point reaches the size set by the grid window, it is recognized as a ground point; If not achieved, adjust the window size again for iterative operations [16, 17].

iv. Perform steps ii) and iii) on all point cloud data until there are no classifiable point cloud data.

v. As the iteration progresses, perform steps i) and ii) on the unclassified point clouds, gradually adjusting the grid size until it meets the set size requirements.

vi. After reaching the set grid size, stop iteration and identify the remaining unclassified point cloud data as on-site terrain points.

3.3 Point cloud filtering algorithm based on improved surface coverage type

3.3.1 Technical route

3D laser scanning equipment can not only obtain point clouds but also digital image data. The main idea of the point cloud filtering algorithm based on improved surface coverage types is to classify surface cover in a region based on digital images [18]. For exposed surfaces, no filtering is performed; for buildings, classify and remove building point clouds; and for high, medium, and low vegetation, classify and remove vegetation point clouds. Then, we manually classify and inspect the point clouds with the assistance of images. After measuring the accuracy of the profile detection, we complete the point cloud filtering process. The technical route is shown in Figure 2.

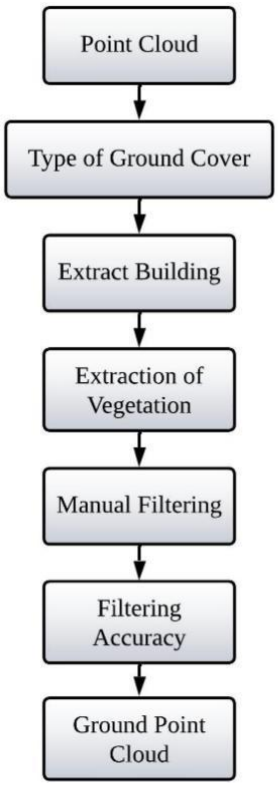

Figure 2: Technical roadmap of point cloud filtering algorithm based on improved surface coverage type

3.3.2 Classification of surface cover types

According to the type of surface coverage, the extraction of non-ground points is shown in Figure 3.

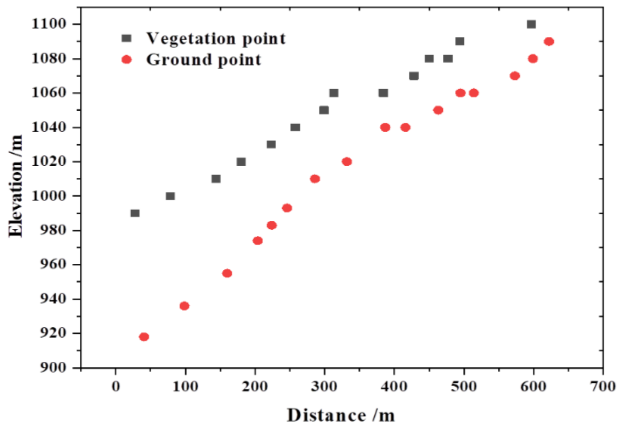

Figure 3: Removing Non-Ground points

4 Experiments

The experiments aim to validate the efficacy of the proposed point cloud filtering algorithm in mountainous terrain. The study uses a chosen area to compare the results of the new algorithm with those of older methods. It focuses on checking the accuracy of profile overlay and elevation. These experiments serve to affirm the algorithm's performance and its potential applications in complex topographies.

4.1 Accuracy evaluation

The improved point cloud filtering accuracy is more intuitive through profile comparison and meets the needs of engineering applications.

4.1.1 Comparison of profile overlay

Select a typical area and compare it with the measured profile and the gradually encrypted triangulation filtering algorithm, as well as the point cloud filtering algorithm based on the improved surface coverage type, as shown in Figure 4.

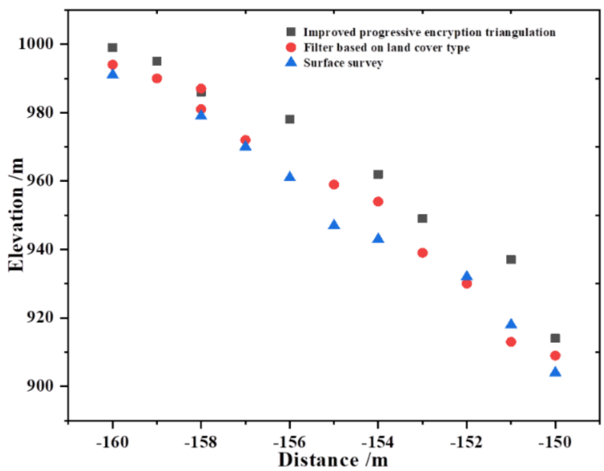

Figure 4: Plot of point cloud filtering algorithm

From Figure 4, it can be seen that the progressive encryption triangulation filtering algorithm is significantly lower than the measured ground line, while the point cloud filtering algorithm based on the improved surface coverage type is located in the middle of the ground line [19].

4.2 Evaluation of profile elevation accuracy

Select typical profiles, and compare the elevation of the profiles intercepted by the progressive encryption triangulation filtering algorithm and the point cloud filtering algorithm based on improved surface coverage types with the measured ground profiles at the same distance [20]. The distribution of their differences is shown in Figure 5, and the statistical results of elevation accuracy are shown in Table 1.

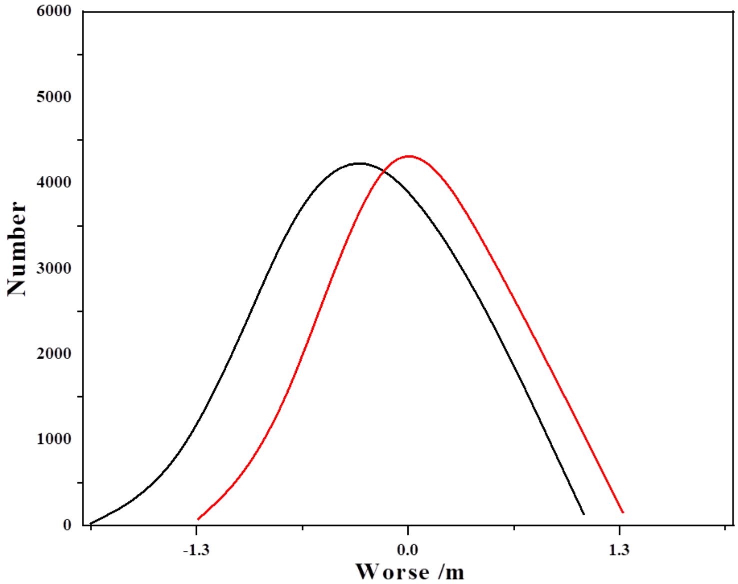

Figure 5: Distribution of profile elevation difference of point cloud filtering algorithm

Table 1: Statistics of profile elevation accuracy

Method	Check the Number	Mean value/m	Mean square error/m
Gradually encrypted triangular network filtering	10863	-0.45	0.71
A Point Cloud Filtering Algorithm Based on Improved Surface Coverage Types	10863	-0.06	0.45

Table 2: Comparative analysis of point cloud filtering algorithms

Parameter	Improved Algorithm	Conventional Algorithm
Ground Point Cloud Deviation	Minimal	Significant
Average Elevation Difference (m)	-0.06	-0.45
Mean Square Error (m^2)	0.45	0.71
Applicability in Mountainous Terrain	High	Limited
Automation Level	High	Moderate
Extraction Accuracy	Superior	Lower

From Figure 5 and Table 1, it can be seen that the average difference in profile elevation of the progressive encryption triangulation filtering algorithm is -0.45 m, which is significantly negative; The average elevation difference of the point cloud filtering algorithm based on improved surface coverage type is -0.06 m, which is close to zero. The mean square error in elevation is 0.71 m and 0.45 m respectively. The accuracy of the point cloud filtering algorithm based on improved surface coverage type is better than that of the progressive encryption triangulation filtering algorithm.

Table 2 compares the results between the proposed improved algorithm and a conventional algorithm in the context of mountainous terrain surveying. The improved algorithm demonstrates minimal deviation from the measured ground profile, yielding an average elevation difference of -0.06m and a mean square error of 0.45m. In contrast, the conventional algorithm exhibits significant deviations, with an average elevation difference of -0.45m and a mean square error of 0.71m. The Improved Algorithm showcases superior applicability, high automation, and enhanced extraction accuracy for complex mountainous landscapes.

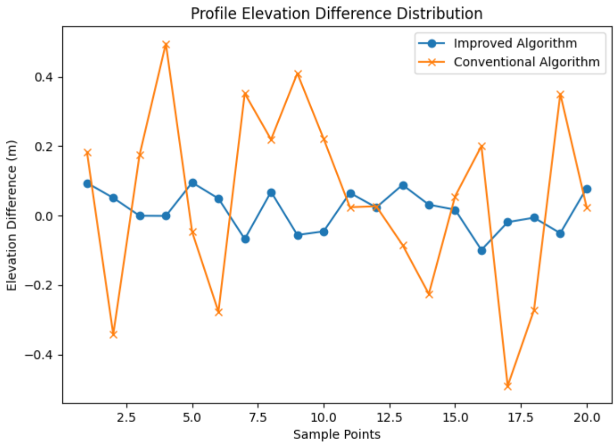

Figure 6: Profile elevation difference distribution

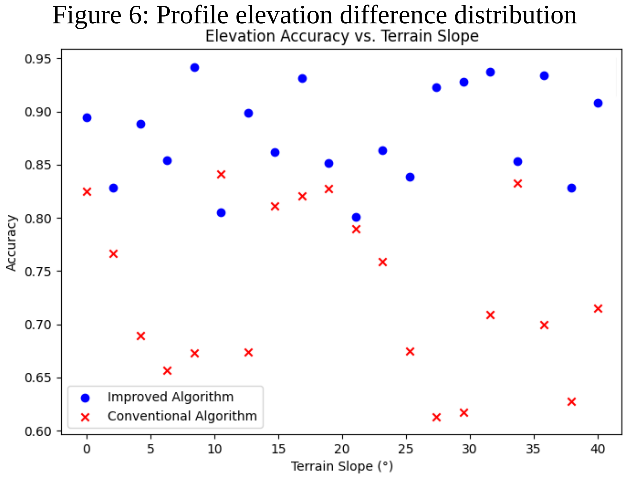

Figure 7: Elevation accuracy vs Terrain slope

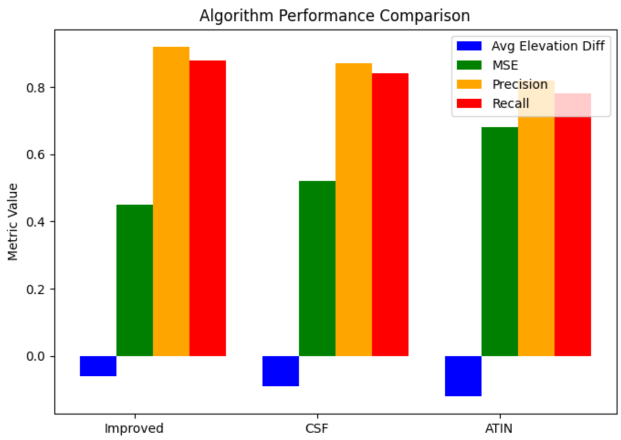

Figure 8: Performance comparison

Figure 7 compares the elevation differences between the proposed improved algorithm and the conventional algorithm [12] across 20 sample points. The line for the improved algorithm fluctuates within a much smaller range, between approximately -0.1 and 0.1 meters, indicating that it closely aligns with the real ground profile, with minimal deviations. In contrast, the conventional algorithm exhibits a wider range of deviations, spanning from -0.5 to 0.5 meters, indicating that it is less accurate and more prone to over- or under-estimation of ground points. It is observed from this analysis that the improved algorithm provides more consistent and reliable results in terms of filtering ground points in mountainous terrains, as it maintains lower elevation deviations compared to the conventional approach. Figure 8 illustrates the relationship between terrain slope (in degrees) and the accuracy of both the improved algorithm and the conventional algorithm. The plot shows that the improved algorithm maintains high accuracy (above 80%) even as the terrain slope increases, which is critical in mountainous regions where slope variability is common. The conventional algorithm, on the other hand, shows a noticeable drop in accuracy as the slope increases, with accuracy values declining below 70% in steeper terrains. This suggests that the improved algorithm is better equipped to handle varying terrain slopes, maintaining higher levels of accuracy even in more challenging, steep areas. In contrast, the conventional algorithm struggles with higher slopes, reducing its overall reliability. Figure 9 compares the performance of three algorithms—Improved Algorithm, Cloth Simulation Filtering (CSF), and Adaptive TIN (ATIN)—using four metrics: Average Elevation Difference, Mean Square Error (MSE), Precision, and Recall. The improved algorithm has the lowest average elevation difference (-0.06 m) and MSE (0.45 m^2), indicating that it is the most accurate and least error-prone method. CSF and ATIN have higher elevation differences and MSE values, which shows that while they are effective, they don't perform as well as the improved method in complex terrains. In terms of precision and recall, the Improved Algorithm again outperforms, with values of 92% and 88%, respectively. These high values indicate that it can identify ground points with both high accuracy and completeness. CSF and ATIN, while still performing well, show lower precision and recall, making them slightly less reliable.

5 Conclusion

The maturation and widespread adoption of 3D laser scanning technology have significantly impacted various fields, including forestry, surveying, water management, and energy. However, traditional ground-point filtering methods face limitations, such as being labor-intensive, low in accuracy, and underperforming in mountainous terrains. These limitations become more apparent as the demand for digital twin watershed construction grows, surpassing the capabilities of conventional filtering methods in addressing the expanding needs of mountain river surveying and mapping. In response to these challenges, this study introduces a novel point cloud filtering approach based on surface coverage types. Through qualitative and quantitative comparisons with established progressive encryption triangulation filtering algorithms, the following conclusions are drawn:

- ***i.*** Traditional filtering methods that use the grid's lowest point as the ground seed consistently underestimate ground points in mountainous point cloud filtering when compared to actual ground points.
- ***ii.*** The proposed point cloud filtering method, based on surface coverage types, challenges conventional approaches by leveraging well-established algorithms, particularly those used for vegetation and building extraction. This results in more efficient removal of non-ground points and improved filtering performance.
- ***iii.*** The point cloud filtering algorithm based on surface coverage types shows better alignment with measured ground profiles after filtering than the progressively encrypted triangulation filtering algorithm. The average elevation difference approaches zero, demonstrating smaller errors and enhanced filtering accuracy.
- ***iv.*** The proposed surface coverage-based filtering method demonstrates excellent applicability, high automation, and superior accuracy in mountainous terrains, offering an innovative solution for filtering point clouds in complex mountainous environments.

In summary, the surface coverage-based point cloud filtering method not only addresses the shortcomings of existing techniques but also offers a more efficient and automated solution for the unique challenges posed by mountainous terrains in surveying and mapping. In the future, the integration of artificial intelligence and machine learning techniques could further enhance the adaptability and effectiveness of this method in challenging mountainous environments.

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